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An analysis of premium payments as a mechanism for securing preferential service in cloud manufacturing

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Abstract

Paying a premium in a cloud manufacturing free market environment will benefit a customer during steady state scenarios, however during disruption this benefit diminishes to zero; dependent on the degree of disruption. These customers will recover quicker from disruptions, but the returns are small compared to the relative increase in cost. A cloud manufacturing scenario without contracts or preferential supply acts as a free market, this significantly increases supply chain risk. The predominant mechanism available to mitigate supply chain risk is the willingness to pay a premium. Agent-based simulation modelling experiments investigated this scenario using an extension of anarchic manufacturing for scheduling and control. The experiments induced a disruptive demand-side step change in requirement mix of capabilities and volume demanded by all customers. One customer was willing to pay a significant premium to the others. The waiting time (non-operating time) was analysed as the benefit and indicator for supply chain performance. The job cost for the customer willing to pay a premium relative to other customers and the relative waiting time were analysed during steady state, disruption, and recovery periods.

Keywords: Cloud manufacturing; scheduling and control; agent-based simulation

1. Introduction & background

Currently Cloud Manufacturing (CM) is proposed for the future of manufacturing, enabling mass customization through the utilization of a diverse and plentiful range of resources. CM environments can replicate a free market, if they are devoid of contracts or preferential supply; this has a significant impact on supply chain risk which cannot rely on traditional mechanisms. Paying a premium for services is seen as the predominate mechanism available to mitigate against supply chain risk.

CM is a recent smart manufacturing paradigm, created from a vision for customer-centric manufacturing that exploits on-demand access to shared resources for optimal resource loading [1]. Operating on a cloud platform by providing access to a network of distributed but virtualised manufacturing capabilities as services, most likely through a cyber-physical system [2]; this is likely to be enabled using cloud computing [3] and internet of things (IoT) technologies [4]. CM's proposed benefits are wide ranging depending on its purpose, the predominate benefits are; improving capacity utilization through resource sharing [5], allowing smaller manufacturers a competitive platform through collaboration [6], facilitating operations for a community of enterprises with a specific shared interest [7], and dynamically manage a distributed supply chain in a private cloud [8]. The envisaged sharing of resources and free transferring of jobs, in a large pool of enterprises, is likely to operate as a free market; due to the lack of customer preference and distributed structure where no individual enterprise has monopolistic power.

CM scheduling and control is highly difficult and complex, the traditional and smart manufacturing scheduling and control problems are extended due to CM characteristics; two key

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features are the multiple categories of stakeholders with autonomous decision-making and individual objectives, and an enterprise's freedom to participate or withdraw dynamically from the CM platform [9]. Operational structures have not been thoroughly evaluated, however centrally operated, free market structures and Service Level Agreements (SLA) [10] have been proposed as possible solutions [6]. These structures must provide high flexibility, which is likely to be facilitated through decentralized decision making. The customer to supplier and inter-supplier relationship will change in a highly flexible and dynamic environment, particularly for free market and centralized structures where direct customer to supplier relationships are temporary and not developed.

There is a large impact on supply chain risk management on moving to a CM platform; suppliers can be any participant in a potentially transient supplier population due to dynamic participation. Traditionally supply chain risk management is achieved through many mechanisms, two key ones are increasing flexibility and controlling/sharing/transferring the risk through vertical integration, contracts and agreements [11]; in CM flexibility increases, however without SLAs and contracts, risk increases dramatically. In free markets, customers view the willingness to pay a premium as the predominate method to secure the supply chain.

This study evaluates a free market CM environment with heavy demand side disruptions and investigates whether the willingness to pay a premium is sufficient to create supply chain security.

The scenario is modelled using anarchic manufacturing [12] which employs a distributed free market, by allowing system elements autonomy and authority to communicate to each other and make decisions. An agent-based model is created on the AnyLogic platform; agent-based decentralised systems for manufacturing is an increasingly researched opportunity [13].

2. Experimental Framework

The experiment investigates a cloud manufacturing free market environment with a defined number of customers and suppliers, representing a CM environment devoid of contracts or preferential partnerships. The predominate mechanism available to customers to reduce supply chain risk is the willingness to pay a premium to secure the services of suppliers. The benefit modelled is a reduced waiting time for operations; quality is not investigated, all operations are assumed to have 100% yield.

The model's free market structure uses customers that create jobs periodically, these are supplied with a currency and a number of predetermined operations of a randomly allocated capability and duration to fulfill. Jobs autonomously negotiate their way through suppliers that offer services to complete operations. Suppliers are initially given two Machine Tools (MTs) of a random capability, they periodically assess whether to sell or invest in additional MTs of a specific capability and proceed to do so. Performance is measured as a customer's job cost and waiting time for operations. Fig. 1 diagrammatically depicts the model structure, where there are multiple customers with jobs negotiating their way round suppliers, who fulfil operations via MTs.

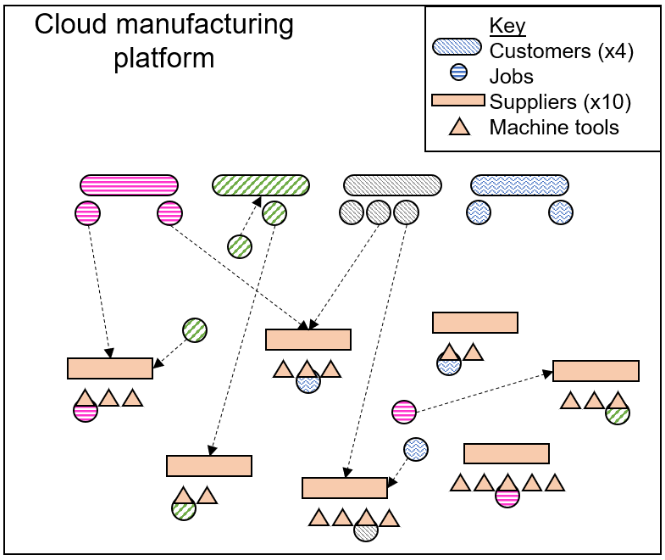

Fig. 1. Model schematic diagram.

Anarchic manufacturing [12] was used as the basis for scheduling and control, providing a free market environment and allowing jobs to negotiate directly with suppliers on a low level.

Fixed parameters ensured stability during simulation experiments, even after a step change disruption. Key fixed parameter levels are highlighted in Table 1.

Table 1. Experiment fixed parameters.

Experiment fixed parameter	Value
No. capabilities modelled	4 (A-D)
Operations/job	4
Average operation duration (random uniform distribution)	15 (U[12,20])
No. customers	4
No. suppliers	10
Initial no. MTs/supplier	2
Customer requested MT utilisation	90%
Currency/operation, customers 1-3	40
Currency/operation, customer 4	80
Supplier invest demand/supply ceiling ratio	1.3
Supplier sell demand/supply floor ratio	0.7

The two variable parameters both change the customer's distribution of requirements, through mix of capabilities and volume of jobs; all customers followed the same demand. The first variable parameter, α, changed the requirement mix, all experiments had four capabilities, but demand started with 50% for capabilities A & B and 0% for C & D. Each simulation run was 3,000t in duration with disruption occurring at 2,000t, the requirement mix distribution post disruption is displayed in Table 2, and Fig. 2 graphically displays the requirement mix step change at t = 2,000t for α=2 (25% change). The second parameter, β, increases the volume of jobs from each customer by: 0, 25%, 50%, 100%. For all experiments the fourth customer was provided with twice as much currency to each of its jobs for negotiating purposes.

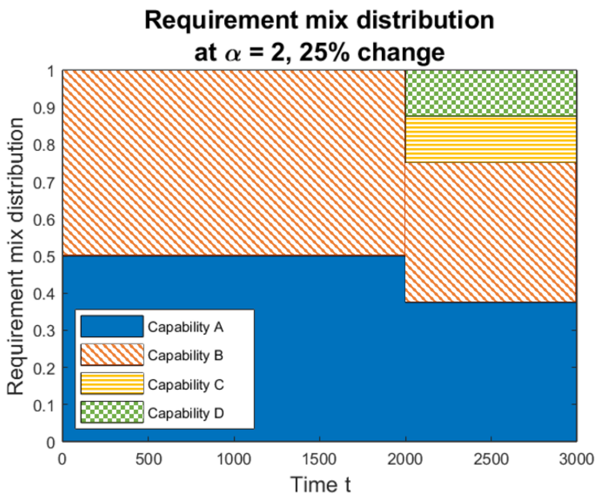

Fig. 2. Requirement mix distribution for α=2, 25% change.

16 experiments were run at each combination of α and β with 100 iterations, each iteration used identical random number inputs, affecting: operation duration and capability, location of customers and suppliers, assignment of initial MT capability. AnyLogic 8 was used, utilizing an agent-based framework with discrete event decision making within agents.

Table 2. Requirement mix distribution disruption.

Parameter level (α, % change)	Requirement mix distribution post disruption			
	A	B	C	D
α=1, 0	50%	50%	0	0
α=2, 25%	37.5%	37.5%	16.7%	16.7%
α=3, 50%	25%	25%	25%	25%
α=4, 100%	0	0	50%	50%

Customer focused job waiting time and cost metrics were recorded, to follow the demand side disruption and customer centric CM paradigm. Waiting time was used instead of overall lead time, to exclude the random variability in operation durations. MT utilization and overall system Work In Progress (WIP) were analysed to ensure that all runs completed successfully and as expected.

In anarchic manufacturing [12], jobs are provided currency and negotiate with suppliers with the appropriate capability to fulfil its next operation. Jobs allocate a proportion of its currency it is willing to spend on its next operation, suppliers evaluate a cost to bid with from utilization, current job queue and expected future demand. If the most suitable bid, considering cost and transportation time, is not below the job's cost threshold, suppliers and the job go into another round of bidding. Between bidding rounds a job lowers its threshold and suppliers increase their bid. If no supplier is cheap enough after five rounds of bidding, the job searches elsewhere in the environment and retenders for more bidding. A heuristic allocates jobs to MTs within a supplier, selecting the next available MT by the shortest queue length.

Extensions to anarchic manufacturing, including the enhanced bidding mechanism by Ma *et al.* [14], were incorporated in this study to accommodate the supplier's dynamic participation. This was achieved by informing suppliers' decision making for investing or selling MTs of specific capabilities; this stems from customers publishing the ratio of current and forecasted demand against supply. Customer k evaluates a demand/supply ratio for capability j, ω_{jk}. The demand is based on the customer's current jobs outstanding and forecasted future jobs, i, in a time period, t_p, at a time horizon, t_h, requiring capability j, J_{kij}, multiplied against the average operation duration, t_o. The supply considers the current number of MTs m of capability j, R_{mj}, and considers the current operation durations and equivalent future machining time in t_p; this is weighted against the supply available to the customer based on the recent proportion of machines the customer used in the past 200 operations globally, ρ_k. The overall ratio is altered for some redundancy against the requested MT utilization, φ_k.

$$J_{kij}(t) = \begin{cases} 1 & \text{if job } i \text{ needs capability } j \text{ and } t = t \\ 1 & \text{if job } i \text{ needs capability } j \text{ and } t_p < t < t_h + t_p \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

$$R_{mj}(t) = \begin{cases} 1 & \text{if MT has capability } j \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

$$\omega_{kj}(t) = \frac{1}{\varphi_k} \cdot \left(\frac{t_o \sum_{i=1}^{n_c} J_{kij}(t)}{(t_o + t_p)\rho_k(t) \sum_{m=1}^{n_n} R_{mj}(t)} \right) \quad (3)$$

Where n_c is the number of jobs in the system and n_n is the number of MTs in the system.

Suppliers weight the customer demand/supply ratio for each capability against the number of operations the supplier has completed for that customer within the past 50 operations. This provides a weighted decision for suppliers, with the recent past being an indicator for the future. If the highest weighted demand/supply ratio exceeds a threshold a MT will be invested in if there is sufficient cash; cash is accrued from completing operations. Similarly, if the lowest ratio falls below a selling floor, a MT of that capability is sold, and half the initial investment cost is accrued as a crude depreciation cost. After an investing or selling decision is made, a reevaluation of the demand/supply ratios is made after a short hesitation period, to counter short-lived changes and volatility.

There is a slight alteration from Ma *et al.*'s extended bidding system [14], suppliers instead of calculating the expected queue length consider the customer weighted demand/supply ratio. Additionally, for jobs the expected cost per operation is based on the average recent cost for that capability for the relevant customer.

3. Results & discussion

Experimental results, recording job cost and job waiting time, show that in a steady state there is a significant benefit from a willingness to pay a premium (customer 4), reflected as a reduced waiting time, however during disruption there is diminishing to zero benefit dependent on the level of disruption. Table 3 links experiment number to the relevant variable parameter levels, Fig. 3 plots the mean and 95%

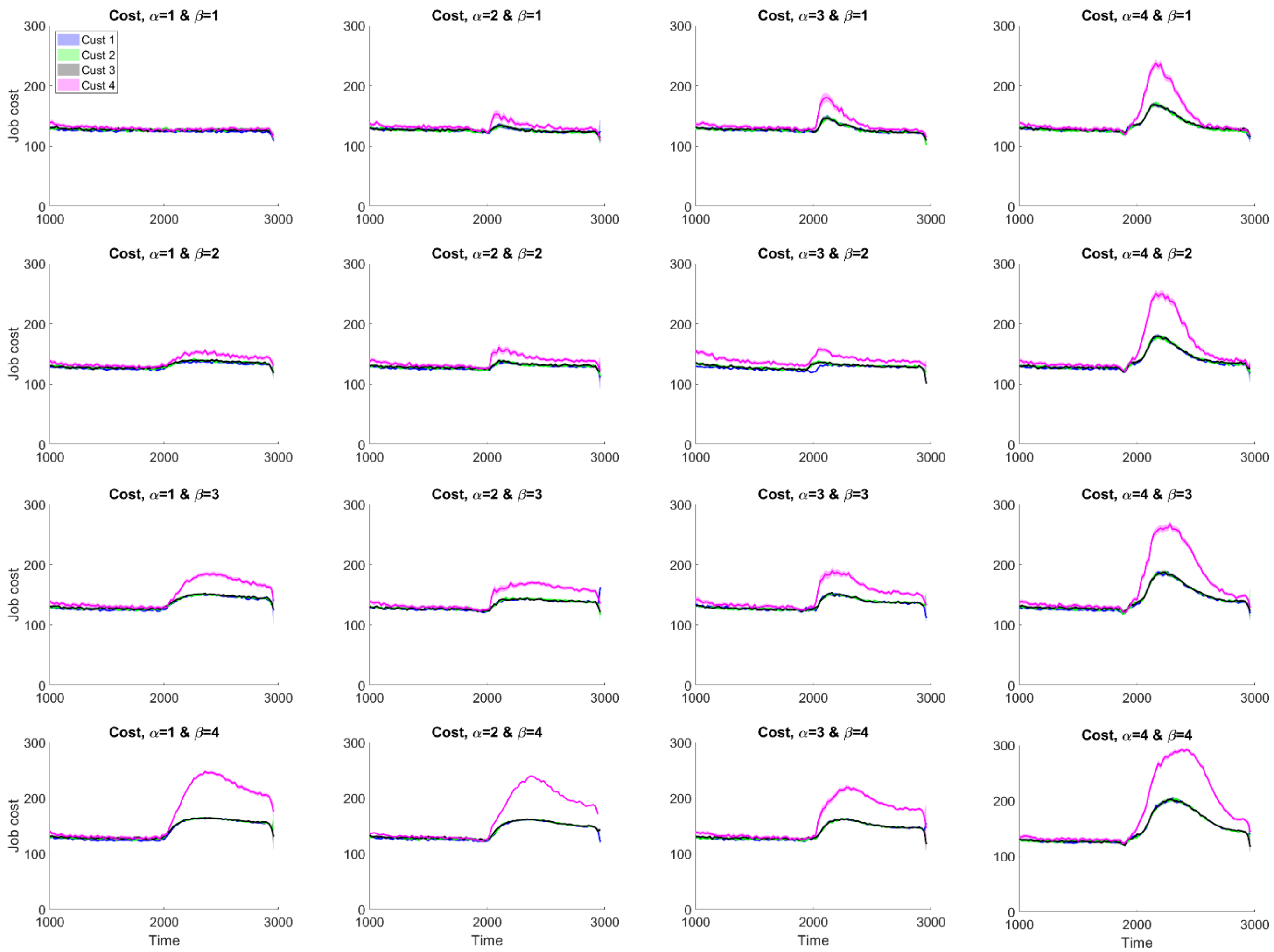

Fig. 3. Customer job cost, all experiments.

confidence interval of the mean as a translucent area for job cost and Fig. 4 for job waiting time for all experiments.

Table 3. Experiment no. parameter levels.

Exp. no.	α=1	α=2	α=3	α=4
β=1	1	2	3	4
β=2	5	6	7	8
β=3	9	10	11	12
β=4	13	14	15	16

During the initial steady state period, 1,000-2,000t after simulation ramp up, there is a distinct benefit of a reduced waiting time without a significant increase in cost for customer 4 who is willing to pay a premium; this is seen in Fig. 3 for waiting time, for experiment 16, as compared to Fig. 4 showing cost. In Fig. 5 to Fig. 7 the relative increase of mean cost for customer 4 against customers 1-3 is plotted horizontally against its relative benefit (decrease) in mean waiting time in the stated period. In the early steady state phase there is a significant benefit with all experiments clustered in a low relative cost and high benefit, in the recovered state there is a benefit, although not universal, shown in Fig. 7.

During disruption periods there is a clear reduction in benefit whilst relative cost significantly increases. Fig. 5, which is immediately after the disruption, roughly shows that the relative benefit reduces inverse proportionately to the increase in relative cost as parameter levels increase. This is predominately governed by the requirement mix disruption, α; as noted by experiment numbers 4, 8, 12 & 16, where α=4 a 100% change, is in the worst performing area. It appears that volume disruption, β, has a reduced impact. During the recovery phase there is a recovery in benefit, measured as a larger relative decrease in waiting time for customer 4, however still a large relative cost incurred; this is shown by the results in Fig. 6 with some experiments showing a relatively high cost and benefit.

These results suggest that in a cloud manufacturing environment, where there is a flat structure without preferential relationships amongst participants which subsequently acts as a free market, paying a premium does pay off in a steady state static environment. However, with a demand side disruption the willingness to pay more will be taken without significant benefit relative to the cost of those who are unwilling. Performance is relatively better, however on an absolute basis it is still very poor. The rate of recovery is marginally better,

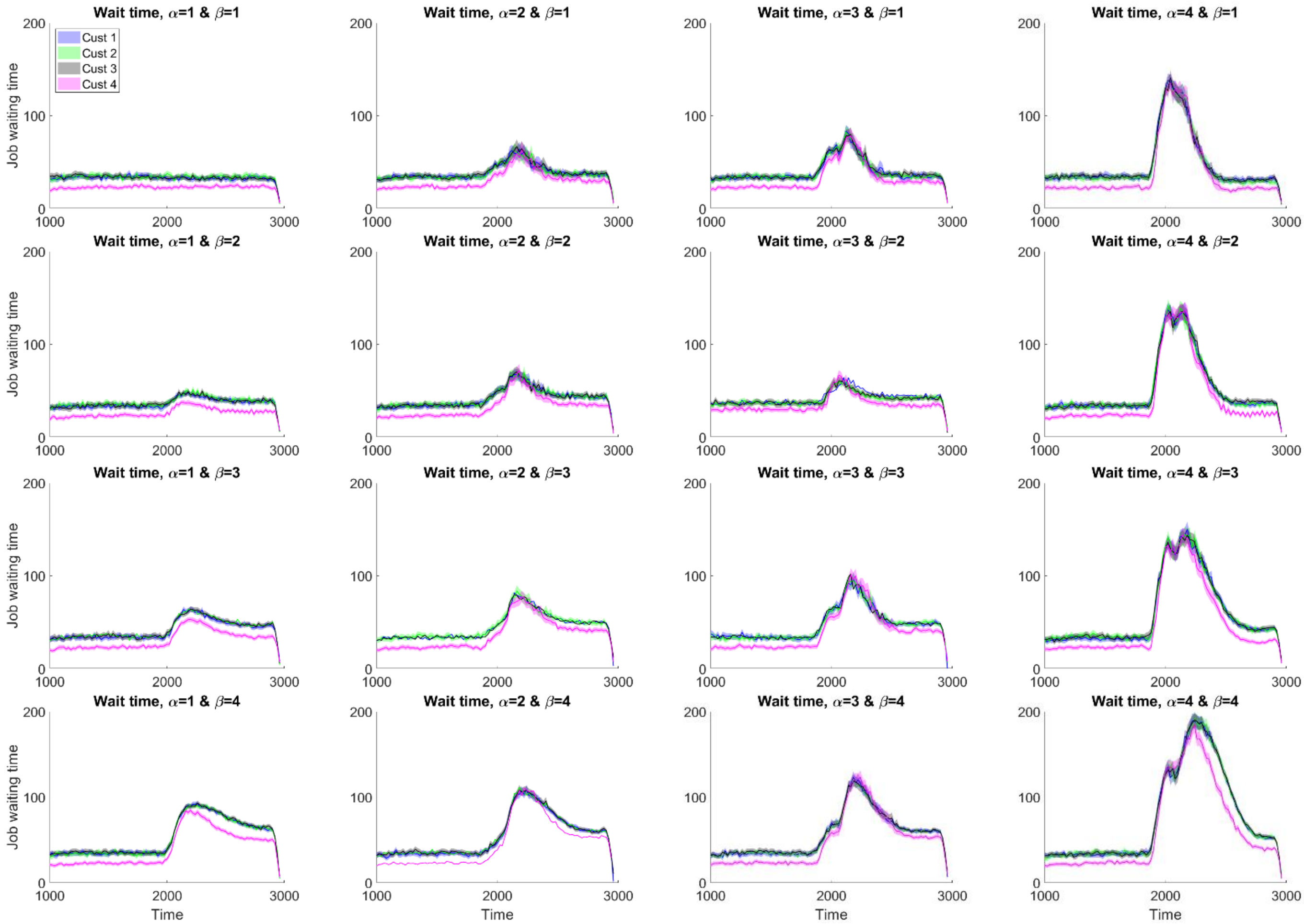

Fig. 4. Customer job waiting time, all experiments.

however there is no guarantee, and little indication, of preferential treatment for paying a premium.

4. Conclusion

This paper evaluates a cloud manufacturing environment, where enterprises operate without contracts or preferential relationships. In this environment paying a premium is the predominate method to improve the services an enterprise receives. A simulation modelling experiment evaluates whether being willing to pay a premium pays off when there is significant demand side disruption; this disruption is simulated as changing the requirement mix of capabilities and increasing the volume of jobs. It is concluded that under steady state

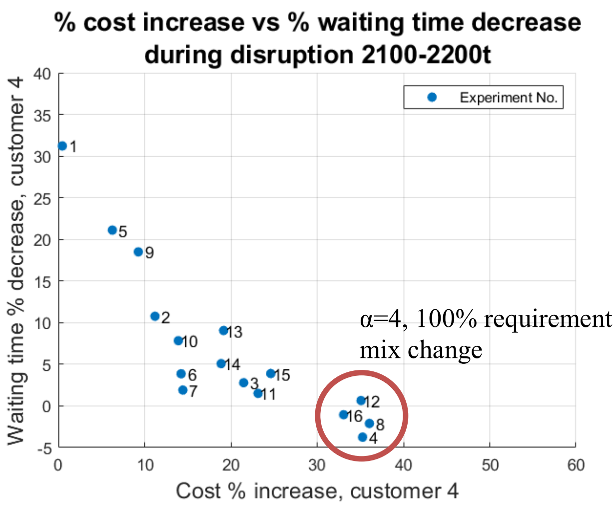

Fig. 5. During disruption relative cost vs relative waiting time.

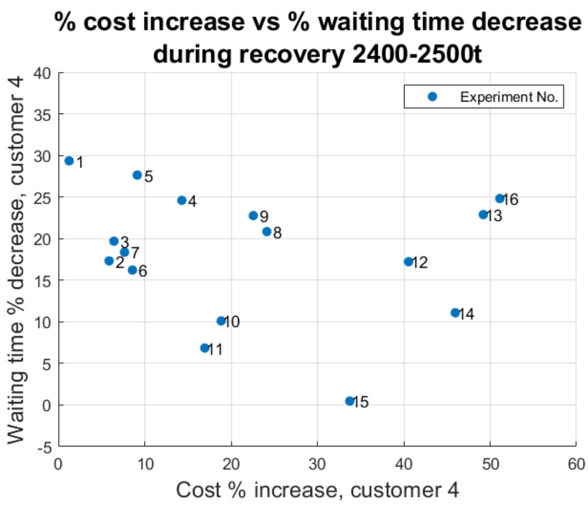

Fig. 6. During recovery relative cost vs relative waiting time.

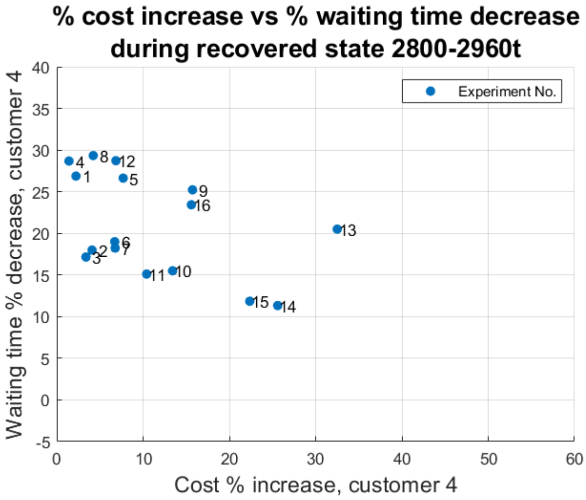

Fig. 7. During recovered state relative cost vs relative waiting time.

circumstances there is a significant return for being willing to pay more as waiting time reduces, however under disruption all customers suffer and there is a proportional decrease in benefit to the rise in cost as disruption increases; particularly prevalent in requirement mix changes. This suggests that under certain CM circumstances that mimic a free market, being willing to pay a premium is an insufficient supply chain risk management mechanism. The implications of this are that more formalized mechanisms are required to manage CM, and enterprises will be unwilling to enter a CM environment which is purely a free market due to high supply chain risk. The likely solution to this is using service level agreements between participants, which guarantee service provision for an explicit duration, this however restricts enterprises and can lead to under-utilized resources through hoarding; this is against the CM ethos and objective to maximise efficiency through resource sharing.

Future work will evaluate whether SLAs are suitable for the CM environment, or whether a free market environment despite its volatility is best used. Both guarantee participant autonomy, to accept or reject work, rather a centralized system will not.

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